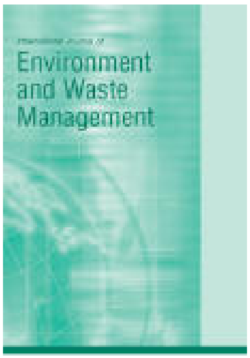
INDERSCIENCE PUBLISHERS
Linking academia, business and industry through research



International Journal of Environment and Waste Management

ISSN online: 1478-9868 - ISSN print: 1478-9876
https://www.inderscience.com/ijewm

Evaluation of Hunan Province's agricultural productivity based on the TOPSIS model

Zhou Ziying

DOI: 10.1504/IJEWM.2026.10077860

Article History:

Received:	22 October 2025
Last revised:	01 December 2025
Accepted:	01 December 2025
Published online:	07 May 2026

Evaluation of Hunan Province's agricultural productivity based on the TOPSIS model

Zhou Ziying

School of Business,
Hunan Institute of Engineering,
Xiangtan, Hunan 411104, China
Email: zhouzy6662025@163.com

Abstract: This study evaluates agricultural productivity in Hunan Province using the TOPSIS model, integrating multiple methodologies for a comprehensive assessment of regional development. A five-dimensional evaluation framework is established based on resource endowment, production capacity, agrarian organisation, overall development, and market competitiveness. The model incorporates weights derived from the analytic hierarchy process (AHP), CRITIC, entropy weighting, and game theory to ensure balanced and accurate results. Findings reveal significant regional disparities: Hengyang and Yiyang lead due to favourable agro-ecological conditions and strong industrialisation, while Xiangtan and Zhangjiajie lag due to limited mechanisation and rapid urbanisation. Mechanisation, irrigation, and intensive farmland management emerge as key drivers of agricultural modernisation. The study offers valuable insights into spatial patterns of agricultural productivity and provides policy recommendations for resource allocation, structural optimisation, and rural revitalisation – offering broader implications for other regions facing similar developmental challenges.

Keywords: agricultural productivity; TOPSIS model; analytic hierarchy process; AHP; entropy weighting; game theory; regional disparities; mechanisation; irrigation; spatial analysis; rural development.

Reference to this paper should be made as follows: Ziying, Z. (2026) 'Evaluation of Hunan Province's agricultural productivity based on the TOPSIS model', *Int. J. Environment and Waste Management*, Vol. 39, No. 5, pp.1–18.

Biographical notes: Zhou Ziying graduated from Hunan Agricultural University in 2012 with land resource utilization and information technology major, currently she works in Hunan Institute of Engineering as an associate professor in the School of Business. Her main research interests are agricultural economic management.

1 Introduction

Modernisation in the Chinese style brings a new way of civilisation, where the protection of cultivated lands is crucial. It explores its theoretical implications in this paper, with special focus on the scientific support of geography. The major findings emphasise the proper utilisation of cultivated land resources, their quality, quantity, and ecological sustainability, given the critical role in modernisation. To do this, it is necessary to incorporate different methods of research. The change in the direction of research in resource geography is consistent with the objectives of modernisation, as it focuses on the evolution of cultivated land resources via a problem-process-mechanism-response paradigm to facilitate decision-making. Moreover, the modernised framework on cultivated land protection entails the analysis of national circumstances, theories, directions, and technology, the development of a strategic spatial framework based on classification and regional management policies, and the framework as a guide regarding the improvement of the cultivated land protection theory and practice in China (Santos-Martín et al., 2019; Xiaobin et al., 2022). Nowadays, the optimisation of the spatial distribution of agricultural productivity is no longer limited to simple technical adjustment at the level of agricultural production, but has risen to a strategic height of solving resource and environmental constraints and ensuring national food security, and has become a key factor that determines the direction of agricultural development (Pandey and Pandey, 2023). Extensive research has been conducted both domestically and internationally on the evaluation and optimisation of agricultural productivity. These studies primarily focus on the measurement and assessment of natural, economic, technological, and comprehensive agricultural productivities. The key findings are summarised below:

1 Agricultural natural productivity focuses on the relationship between crop genetic yield potential and the productivity capacity of agricultural resources, serving as the foundational basis of agricultural output. As early as the 1990s, agronomists conducted extensive research on crop genetic yield ceilings and agricultural resource potential. Notable studies include Yan et al. (2025). In China, scholarly inquiry into agricultural productivity emerged in the 1980s, with Gu Huanzhang and Zhu Xigang recognised as pioneering researchers in this field (Zhang, 2022). Recent innovations are represented by Kailaku et al. (2025), who proposed a smart agriculture framework featuring real-time monitoring of Indonesia’s food supply chains. This approach effectively identifies and mitigates supply chain inefficiencies through technological integration.

2 Research on agricultural comprehensive productivity in China has yielded significant findings through empirical investigations: Guo et al. (2020) created an index system of new agricultural quality productivity utilising panel data of Chinese provinces from 2012 to 2022, and constructed the index system from four dimensions: agricultural science and technology, labour factors, industrial upgrading, and agricultural ecology.

In summary, the research on methods for measuring and evaluating agricultural productivity is quite extensive. There are few publications on the in-depth appraisal method for regional characteristic industries, which considers resource endowment and input, production level and capacity, agricultural structure layout, comprehensive agricultural development, and agricultural market rivalry. In southern provinces, mountainous, forested, and garden land predominates and arable land is scarce. For instance, the Hunan region, a typical southern agricultural region, faces fragmented arable land resources, a high proportion of mountainous and forested areas, and ecological conservation and industrial growth. Traditional agricultural productivity assessments focus on single production factors or output efficiency, which are unsuitable for Hunan's complex industrial clusters. This study presents a five-dimensional linkage evaluation system that includes resource endowment and input, production level and capacity, agricultural structure layout, complete agricultural development, and agricultural market rivalry. This system uses a 'full-chain, multi-objective' collaborative assessment instead of the 'single-point breakthrough' model of agricultural evaluation to guide the high-quality growth of mountainous agriculture in the south.

1.1 Literature review

Wang et al. (2023) assessed Anhui Province's agricultural water resource carrying capacity using an upgraded TOPSIS model with structural entropy weighting. Water capacity rose from 2000 to 2020. The north dropped while the south rose. Sustainable agricultural development in Anhui requires water, conservation, and premium land management.

Pan et al. (2022) evaluated the regional appropriateness of Chinese agricultural production employing analytic hierarchy process (AHP), spatial autocorrelation, and geographic detectors. The analysis identified a tendency of 'polarisation', indicating greater appropriateness in the southeast and diminished suitability in the northwest. Climate change and urbanisation have significantly impacted agricultural viability globally. The research suggests region-specific strategies to enhance agricultural production areas in response to climate change and urbanisation. Cao et al. (2025) studied new quality production in 31 Chinese provinces' agricultural and rural regions. A strong geographical autocorrelation showed a productivity gradient from east to west. Still, gaps are shrinking. Northern regions struggle, eastern regions lead, centre regions advance, and western regions close the gap. Using spatial analysis, this work improves agricultural and rural production studies. Duan and Pan (2024) examined Hunan Province's grain family farm sustainability using survey data and entropy weight TOPSIS. The authors found sustainability discrepancies in Hunan Province's four areas. These issues included water utilisation, soil protection, ecological culture, carbon management, farmer employment, and environmental adaptability. The authors offered ways to support Hunan grain family farms. Krityakierne et al. (2025) examined the shift from traditional to modern farming in Thailand, focusing on supply issues and smallholder poverty. They created a multi-goal enhancement model for crop allocation using GIS and economic data. Its effectiveness was displayed in Chiang Mai, optimising land use for corn, cane, and rice within budget constraints. This research advances Thai agriculture, supporting sustainability. Yanbo et al. (2023) also devised a framework, model, and policy for resolving land use conflicts along the Yellow River Delta, drawing on ecological protection, agriculture, and urban advancement. They adopted a 'rigid constraint' and 'flexible guidance' approach for planning space, encouraging high-quality development by zonation. The study unearthed serious land use conflicts and a need for a coordinated policy to harmonise ecology, agriculture, and urbanisation for sustainable development.

1.2 Research gaps

The agricultural productivity research in Hunan Province indicates some lapses in research. To begin with, knowledge can be gained by comparing the productivity within provinces with similar ecological challenges. Secondly, the use of technologies like precision agriculture and AI could be able to capture their productivity effects in fragmented regions. Thirdly, the long-term effect of climate change in terms of productivity, especially water supply and harvest, is vital to the southern provinces. Besides, it may be possible to introduce sustainability measures like carbon footprint and water productivity to bring in an angle of sustainable production tactics. The other research gap is the analysis of the performance of the existing agricultural policies on market competitiveness and the livelihood of the farms. Other scholars may consider the social impact of the agricultural innovations, such as the migration of farmers to the cities and the distribution of income. Finally, the research on agricultural value chains and the prospects of the local products for market access improvement of farmers could give the region economic development.

1.3 Contributions

This research builds a Hunan Province agricultural productivity evaluation system engaging the top five aspects, namely: resource endowment, production capacity, agrarian structure, overall development, and market competitiveness. Different methods, including AHP, CRITIC, and Entropy Weighting, are deployed to obtain the weights, and then game theory is applied to combine the weights, thus ensuring balanced and accurate results. The study reveals agricultural productivity geographical disparities; thus, it exemplifies the cities of Hengyang and Yiyang as the leading ones that are benefiting from geographical advantages. The findings offer policy advice for agricultural modernisation, such as resource investment growth, structure optimisation, and rural prosperity through specialisation and support of the production policy. This research serves as a source of knowledge about agricultural productivity and a direction for policy improvement not only for Hunan Province but also for other areas with similar agricultural conditions.

2 Research method

2.1 Construction of the appraisal indicator system

Based on existing research in agricultural productivity (Li et al., 2016; Ortiz-Bobea et al., 2021; Zhang, 2022) and the actual conditions of agricultural development in Hunan Province, this study evaluates agricultural productivity through two first-level indicators: agricultural product function and agricultural value function. The agricultural production function indicator covers the following:

1 the evaluation of natural resources that are the basis of agriculture

2 the socio-economic environment that includes the production capacity, technological capability, and agricultural structure

3 the production level and capacity that are the integration of both natural resources and social development elements.

The agricultural value function indicator is mainly composed of the socio-economic environment that includes agricultural output value (measuring the sector's current economic contribution) and market competitiveness (indicating the competitive advantage and adaptability of regional agriculture). As presented in Table 1, Hunan's agricultural productivity evaluation system includes five dimensions with specific indicators: resource endowment and input (seven indicators): effective irrigated area, proportion of cultivated land to administrative area, proportion of irrigated cultivated land to total cultivated land, per capita cultivated land area, overall power of agricultural machinery, fertiliser application per hectare of cultivated land, agricultural machinery power per hectare; production level and capacity (four indicators): three-year average annual growth rate of total agricultural machinery power, grain yield per hectare, cotton yield per hectare, oil crop yield per hectare; agricultural structure (three indicators): proportion of meat production to provincial total meat output, proportion of primary industry employment to total rural population, agriculture's share in total primary industry output value; comprehensive agricultural development (three indicators): per capita disposable income of rural residents, growth rate of primary industry, growth rate of agricultural GDP including ancillary services; market competitiveness (three indicators): proportion of primary industry to provincial GDP, proportion of planting area for the top three specialty crops in total sown area , proportion of agriculture, forestry and water affairs expenditure in general public budget. This comprehensive indicator system maintains consistency with China's statistical standards while ensuring international comparability through standardised measurements. The framework captures both production fundamentals and value creation aspects of agricultural productivity in Hunan Province, providing a robust basis for evaluation and policy formulation.

Table 1 Evaluation indicator of agricultural productivity in Hunan Province

Objective layer	*Criterion layer*	*Indicator layer*	*Unit*	*Positive/negative orientation of indicators*
Agricultural production function	Resource endowment and input	Effective irrigation area x_1	Thousand hectares	Positive
		Proportion of cultivated land to administrative area x_2	%	Positive
		Proportion of irrigated cultivated land to total cultivated land area x_3	%	Positive
		Per capita arable land area x_4	hm^2	Positive
		Overall power of agricultural machinery x_5	KWH	Positive
Agricultural production function	Resource endowment and input	Fertiliser application rate per hectare of cultivated land x_6	kg/hm^2	Negative
		Overall power of agricultural machinery per hectare x_7	KWH/km^2	Positive
Agricultural production function	Production level and capacity	3-year average annual growth rate of total agricultural machinery power x_8	%	Positive
		Grain yield per hectare x_9	kg	Positive
		Cotton yield per hectare x_{10}	kg	Positive
		Oil crop yield per hectare x_{11}	kg	Positive

Table 1 Evaluation indicator of agricultural productivity in Hunan Province (continued)

Objective layer	*Criterion layer*	*Indicator layer*	*Unit*	*Positive/negative orientation of indicators*
Agricultural production function	Agricultural structure layout	Proportion of meat production to provincial total meat output x_{12}	%	Positive
		Proportion of primary industry employment to total rural population x_{13}	%	Positive
		Agriculture's share in total primary industry output value x_{14}	%	Positive
Agricultural value function	Comprehensive agricultural development	Per capita disposable income of rural residents x_{13}	yuan	Positive
		Growth rate of the primary industry x_{16}	%	Positive
		Growth rate of agricultural GDP, including ancillary services x_{17}	%	Positive
	Market competitiveness	Proportion of primary industry in provincial GDP x_{18}	%	Positive
		Proportion of planting area for the top three specialty crops in total sown area x_{19}	%	Positive
		Proportion of agriculture, forestry, and water affairs expenditure in the general public budget x_{20}	%	Positive

2.2 *Determination of indicator weights*

2.2.1 *Determination of weight based on the AHP*

1 Establishing the hierarchical relationship for agricultural productivity in Hunan Province. Based on expert judgment, a pairwise comparison matrix $A = (a_{ij})$ is constructed, where Vaidya and Kumar (2006):

- $a_{ij} > 0$ (all elements are positive)
- $a_{ij} = 1$ (diagonal elements are 1, indicating equal importance of an objective to itself),
- $a_{ij} = 1/a_{ij}$ (reciprocal property, ensuring consistency in comparative judgments).

Here, a_{ij} displays the relative importance of the objective i compared to the objective j.

2 Calculation of subjective weights for evaluation indicators: First, multiply the n row vectors of the judgment matrix A, then take the n. The root of the product to obtain the eigenvector. Finally, normalise the eigenvector to derive the weight vector.

$$K_i = \prod_{i=1}^{n} A_i \tag{1}$$

$$M_i = \sqrt[n]{K_i} \tag{2}$$

$$w_i = \frac{M_i}{\sum_{i=1}^{n}} \tag{3}$$

In the formula: K_i displays the product of row vectors, M_i denotes the eigenvector components, and w_i indicates the weight of each indicator.

3 Consistency track of the judgment matrix. This is a pivotal stage to ensure reasonable weight allocation and logical coherence among the elements in the matrix A. When the order of A is greater than 2, it is vital to compute the consistency index (CI) and the consistency ratio (CR). If CR is less than 0.1, A is considered to have satisfactory consistency, and its weight distribution is acceptable. If this condition is not catered to, the matrix elements must be refined until the consistency requirement is catered to.

$$\lambda \sum_{j=1}^{m} \frac{[Aq]_j}{nq_j}_{\max} \tag{4}$$

$$CI = \frac{\lambda_{\max}}{n-1} \tag{5}$$

$$CR = \frac{CI}{RI} \tag{6}$$

In the formula: $\lambda_{\max}$ displays the peak eigenvalue of the judgment matrix, RI denotes the random index (a predefined constant), and indicates the CR. When $CR < 0.1$, the judgment matrix is considered to have good consistency, meaning the derived weights are reasonable and acceptable.

2.2.2 Weight determination based on the CRITIC method

1 Utilising the constructed evaluation indicator system, the original data matrix X of the agricultural productivity evaluation indicator in Hunan Province is established. The elements of the matrix are represented by x_{ij} and the original data forms a matrix $X(x_{ij})_{mn}$ with m rows and n columns, which can be displayed below:

$$X = \left(x_{ij}\right)_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{7}$$

2 Data standardisation: the evaluation indicators are normalised to the [0, 1] interval, and the standardised decision matrix $Z_{mn} = [y_{ij}]_{mn}$ is constructed. The positive indicators are normalised by equation (8), and the negative ones by equation (9).

$$X_{ij} = \frac{x_{ij} - x_{\min}}{x\min_{\max}} \tag{8}$$

$$X_{ij} = \frac{xij_{\max}}{x\min_{\max}} \tag{9}$$

3 The objective weight is determined, the information quantity of the indicator is determined according to the standard deviation, and the conflict between the indicators is calculated with the help of the correlation coefficient. The formula is as follows (Žižović et al., 2020):

$$s_i = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(X_{ij} - X\overline{ij}\right)^2} \tag{10}$$

$$\rho_{ij} = \operatorname{cov}\left(x_i', x_j'\right) / \left(s_i, s_j\right) \tag{11}$$

$$G_i = s_i \sum_{j}^{n}\left(1 - \rho_{ij}\right) \tag{12}$$

$$\beta_i = \frac{G_i}{\sum_{i=1}^{n} G_i} \tag{13}$$

where s_i and s_J represent the standard deviations of standardised indicators i and j respectively, $X\overline{ij}$ denotes the mean value of X_{ij} ρ_{ij} is the correlation coefficient between the indicator i and indicator j, is the standard deviation of the indicator i and indicator j after standardised treatment, and is the average of the indicator, and β_i is the weight of the evaluation indicator i.

2.2.3 Determination of weights utilising the entropy weighting method

1 According to the normalised indicator values of formula (8) and formula (9), the information entropy of the evaluation indicator is calculated utilising the following formula (Tsai et al., 2008):

$$H_j = -k\sum_{j=1}^{n} f_{ij} \ln f_{ij} \tag{14}$$

$$k = \frac{1}{\ln n} \tag{15}$$

$$f_{ij} = y_{ij} \Big/ \sum_{j=1}^{n} y_{ij} \tag{16}$$

In this formula, H_j displays the information entropy of the j^{th} indicator. When $f_{ij} = 0$, $\ln f_{ij} = 0$.

2 The entropy weight of each evaluation indicator, that is, the information entropy weight, is as follows:

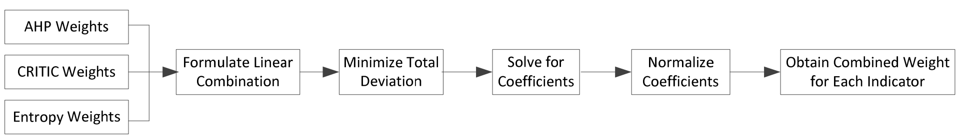
$$p_j = \left(1 - H_j\right) \Big/ \left(m - \sum_{j=1}^{m} H_j\right) \tag{17}$$

In the formula, $0 \le p_j \le 1$, and $\sum_{j=1}^{m} p_j = 1$.

2.2.4 Obtaining the weighted combination

This study employs a game theory-based combined weighting method to balance the subjective and objective aspects of evaluation indicator weights, with the specific procedure detailed in Figure 1. This methodology reconciles conflicts between different weighting techniques by pursuing a Nash equilibrium, achieving an optimal compromise between subjective judgments and objective data.

Figure 1 Flowchart for deriving combined weights using game theory



The procedure comprises three key steps. First, a foundational weight set is established using weights derived from the AHP, the CRITIC method, and the entropy weight method. These vectors constitute the fundamental elements for the subsequent combination. Next, an optimisation model is constructed based on game theory principles to minimise the total deviation between the combined weight vector and each fundamental vector. The optimal combination coefficients are derived by solving the model's first-order derivative conditions and are subsequently normalised. Finally, the comprehensive combined weights are computed through a weighted synthesis of the three fundamental weight vectors using these optimal coefficients. This process yields a final set of weights that effectively integrates both subjective and objective information. The combined set preserves the value of expert judgment inherent in subjective methods while incorporating the data-driven characteristics of objective approaches, thereby establishing a more robust and rational benchmark for evaluation.

2.3 Evaluation of agricultural productivity in Hunan Province by weighted combination

1 Construct the agricultural productivity evaluation matrix X of Hunan Province, standardise the matrix X according to formulas (8) and (9), and obtain the normalised matrix Z of agricultural productivity evaluation of Hunan Province. Multiply the matrix Z with the combined weight matrix W^*, and get the weighted matrix Z', whose elements are Z_{ij} and Z'_{ij}, $Z' = W * Z$.

2 The positive ideal solution matrix Z^+ and a negative ideal solution matrix Z^- of agricultural productivity are constructed by using the optimal value and the worst value of every appraisal indicator, which are expressed as follows (Çelikbilek and Tüysüz, 2020):

$$\begin{aligned} Z^+ &= \left[\max Z_{ij} \big|_{j\in J}, \min Z_{ij} \big|_{j\in J'} \right] \\ &= \left[Z_1^+, Z_1^+, \cdots, Z_m^+ \right] \end{aligned} \tag{23}$$

$$\begin{aligned} Z^- &= \left[\min Z_{ij} \big|_{j\in J}, \max Z_{ij} \big|_{j\in J'} \right] \\ &= \left[Z_1^-, Z_1^-, \cdots, Z_m^- \right] \end{aligned} \tag{24}$$

3 Compute the Euclidean distance between the evaluated object and the positive and negative ideal solutions of agricultural productivity respectively:

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(Z_{ij} - Z_j^- \right)^2} \tag{25}$$

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \left(Z_{ij} - Z_j^+ \right)^2} \tag{26}$$

D_i^- and D_i^+, respectively, represent the Euclidean distance between the evaluation object and the negative and positive ideal solutions.

4 According to the Euclidean distance value, the relative closeness between each assessed object and the ideal solution is computed, which is the development level of agricultural productivity of each evaluation object (Sarkar, 2013).

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{27}$$

In the formula, C_i displays the relative closeness of each evaluation object to the ideal solution.

A higher relative closeness degree of agricultural productivity indicates a more advanced development level. Based on the calculated relative closeness values, agricultural productivity levels are sorted into five tiers: low, moderately low, medium, moderately high, and high. For specific classification criteria, refer to Zhou et al. (2019).

Table 2 Sustainable development level of agricultural productivity

Relative proximity Ci	*Degree*	*Relative proximity Ci*	*Degree*
[0, 0.2)	Low	[0.8, 0.8)	Moderately high
[0.2, 0.4)	Moderately low	[0.8, 1]	High
[0.4, 0.6)	Medium		

3 Empirical research

3.1 Research object

Hunan Province is mountain-based and spans an area of 211,800 km^2. Out of overall land, mountains cover 51.2%, hills and ridges 29.3%, and plains and water together 13.1% and 6.4%, respectively. The province is distributed in the proportions of the classic '70% mountains, 20% water, and 10% farmland'. The geographical framework of 'Three Xiangs and Four Rivers' has led to the development of a unique pattern of regional development. The climate of the subtropical monsoon humid type is typical for Hunan Province. The annual mean temperature veries from 16 to 18°C and the rainfall varies between 1,200 and 1,700 mm per year. The province has a frost-free period of 260–310 days per year. Hunan has been the cradle of rice cultivation for 12,000 years and thus it has been called "When Hunan and Hubei flourish, the nation enjoys abundance". In 2023, the area's cultivated land reached 3.834 million hectares, which is why Hunan has kept its top position as the largest rice-producing region in China. Additionally, it ranks among the national leaders in the production of cash crops such as ramie, tea oil, and flue-cured tobacco.

3.2 Data source

This study employs 14 prefecture-level cities in Hunan Province as research units. The data were primarily sourced from: Comprehensive materials from Hunan's Third National Agricultural Census, provided by the Hunan Provincial Bureau of Statistics, Hunan Rural Statistical Yearbook, county-level statistical data.

3.3 Evaluation indicator weight analysis

According to the constructed agricultural productivity indicator evaluation system and the indicator data of 14 prefecture-level cities, the weight of 20 indicators was obtained by utilising APC, CRITIC, and the entropy weighting method, and then the comprehensive weight of every indicator was attained by utilising the game theory tactic, as displayed in Table 3.

As shown in Table 3, the weight of each indicator for agricultural production functions is 0.673, while the weight of agricultural value functions is 0.372. This indicates that the importance of agricultural production functions in Hunan Province's agricultural ecosystem is significantly higher than that of agricultural value functions. When viewed through the lens of the criteria layer of agriculturally productive functions, the allocations for resource endowment and input, production level and capacity, and agricultural structure stand at 0.300, 0.186, and 0.187, respectively. This suggests that resource endowment and input have the most significant influence, with this aspect having the largest share.

1 Identification of key indicators and policy focus. Based on the combined weights and their policy relevance, five core indicators of greatest significance for policymakers are identified. The share of regional meat output in provincial total demonstrates the highest weight among all indicators at 0.097, serving as a critical measure of regional specialisation and industrial structure. The per capita disposable income of rural

residents, with a weight of 0.085, functions as a livelihood indicator that directly reflects how agricultural development benefits farmers. The growth rate of primary industry carries a weight of 0.063, representing a core metric for dynamically monitoring the sector's development vitality. The overall power of agricultural machinery per hectare holds a weight of 0.055, characterising the technical level of agricultural mechanisation. Finally, the proportion of irrigated cropland area to total cultivated land, with a weight of 0.049, reflects the fundamental capacity of agricultural infrastructure support.

Table 3 Weight values of the agricultural productivity evaluation indicator system

Objective layer	*Criterion layer*	*Indicator layer*	*Weights obtained from AHP*	*Weights obtained from the CRITIC method*	*Entropy weight*	*Combined weights*
Agricultural production function	Resource endowment and input	x_1	0.038	0.041	0.046	0.042
		x_2	0.008	0.050	0.036	0.034
		x_3	0.027	0.051	0.061	0.049
		x_4	0.066	0.048	0.036	0.048
		x_5	0.012	0.049	0.037	0.035
		x_6	0.017	0.049	0.039	0.037
		x_7	0.066	0.052	0.051	0.055
	Production level and capacity	x_8	0.029	0.042	0.026	0.032
		x_9	0.099	0.048	0.029	0.053
		x_{10}	0.053	0.056	0.042	0.050
		x_{11}	0.053	0.045	0.056	0.051
	Agricultural structure layout	x_{12}	0.037	0.051	0.174	0.097
		x_{13}	0.037	0.042	0.025	0.034
		x_{14}	0.074	0.056	0.045	0.056
Agricultural value function	Comprehensive agricultural development	x_{15}	0.138	0.049	0.083	0.085
		x_{16}	0.076	0.063	0.055	0.063
		x_{17}	0.043	0.056	0.027	0.041
	Market competitiveness	x_{18}	0.054	0.052	0.033	0.045
		x_{19}	0.054	0.051	0.061	0.056
		x_{20}	0.019	0.049	0.038	0.037

2 Policy implications of core indicators. These five core indicators reveal Hunan's strategic agricultural development pathways from multiple dimensions. In terms of production functions, the considerable weights of agricultural mechanisation and irrigation guarantee demonstrate the province's strategic emphasis on productivity enhancement through technological modernisation, particularly crucial for its rice-dominated agricultural system. The prominent weight of meat production concentration highlights the essential role of specialised industry development in agricultural structural adjustment. Regarding value functions, the significance of farmer income and industrial growth identifies the ultimate objectives of agricultural development and key monitoring priorities, embodying a development philosophy

that balances efficiency with equity. To systematically enhance agricultural productivity in Hunan Province, we recommend establishing the aforementioned five core indicators as the primary basis for policy formulation and routine monitoring systems, while recognising that the remaining indicators provide indispensable supplementary functions in specific policy contexts and in-depth analyses. These auxiliary indicators offer critical support for regional differentiated policy-making, industrial bottleneck diagnosis, and long-term strategic planning, collectively constituting a comprehensive agricultural policy evaluation framework.

3.4 Comprehensive agricultural productivity level in Hunan Province

We used the comprehensive weights from Table 3 to measure the agricultural productivity levels of 14 prefecture-level cities in Hunan Province by the TOPSIS method. The classification results were based on the standard typology as displayed in Table 4. Significant gradient disparities of comprehensive agricultural productivity in the 14 prefecture-level cities of Hunan Province are well illustrated in Table 4. Hengyang City (0.528) and Yiyang City (0.506) are the two places that pull ahead of the pack thanks to outstanding irrigation infrastructure, concentrated meat industry development, and higher farmer income levels. These regions have effectively capitalised on the natural endowments of the Dongting Lake Plain area by implementing mechanisation, water conservancy construction, and specialised agricultural models, thereby achieving simultaneous improvements in both production efficiency and economic benefits. The intermediate tier of the development bottleneck (0.40–0.50) is formed by 9 cities that constitute the strategic hinterland of agricultural productivity, cities within this tier demonstrate balanced yet unremarkable performance across core indicators. Their development is constrained by multiple factors including insufficient optimisation of the agricultural industrial structure, inadequate cultivation of distinctive agricultural products, and relatively weak agricultural growth momentum. Despite being in the centre of the Changsha-Zhuzhou-Xiangtan city cluster, Xiangtan City comes last with a proximity score of 0.370, underscoring the problems of non-agricultural land usage and agricultural workforce loss during urbanisation. The Wuling Mountains' broken topography and farms limit Zhangjiajie City (0.373) and Xiangxi Autonomous Prefecture (0.389). Despite having potential for unique planting resources, their agricultural output size and mechanisation are far lower than the province average.

Table 4 Comprehensive agricultural productivity levels across prefecture-level cities in Hunan province

City	*Closeness coefficient C_i*	*City*	*Closeness coefficient C_i*	*City*	*Closeness coefficient C_i*
Changsha City	0.497	Yueyang City	0.464	Yongzhou	0.490
Zhuzhou City	0.485	Changde City	0.464	Huaihua City	0.400
Xiangtan City	0.370	Zhangjiajie City	0.373	Loudi City	0.443
Hengyang City	0.528	Yiyang City	0.506	Xiangxi autonomous prefecture	0.389
Shaoyang City	0.427	Chenzhou City	0.444		

3.5 The development level and distribution characteristics of the agricultural production function

TOPSIS was deployed to review the advancement levels of agricultural production functions in 14 prefecture-level cities in Hunan Province, resulting in proximity scores for each city. Based on these scores, the cities were categorised, as displayed in Table 5. The three first-tier (core zone) cities: Hengyang City (0.559), Yiyang City (0.553), and Zhuzhou City (0.516), which have achieved significant development through the ‘geographical location-factor agglomeration-institutional innovation’ triad. Leveraging regional advantages, the following key initiatives should be prioritised: establishing regional deep-processing centres for agricultural products to increase the processing conversion rate beyond 70%, thereby enhancing added value and market competitiveness; strengthening technological empowerment in agriculture through the development of intelligent agricultural machinery research and manufacturing bases, utilising advanced equipment to drive agricultural modernisation; and actively fostering new agricultural business entities to form industrial consortiums that integrate resources for achieving scaled and intensive agricultural development. The seven cities at the prefecture level that make up the second tier (potential tier) are characterised by “large aggregate base but suboptimal structure” which is reflected in their contribution to the total arable land and grain output of the province. They have 68.5% of the province’s arable land and 72.3% of its grain output. Besides, Changde and Yueyang are the two cities that are the flagship national-level commercial grain production bases. The problem is that the industrial chains in these two cities are not very active. Based on the agricultural processing and conversion rate, the two cities only managed an average of 58.6%, which is less than the rates of the first-tier cities like Hengyang City (67.2%) and Yiyang City (63.8%). In the future, these areas will have to invest in the removal of obstacles such as lack of comprehensive and well-developed supply chains and infrastructure that can support them so that scale-driven advantages can be converted into value-driven ones in agriculture. The regions in the third tier (nurturing zone), that is, Xiangxi Prefecture, Huaihua City, Xiangtan City, and Zhangjiajie City, have the double features of “abundant ecological resources and low conversion efficiency”. Their nurturing zone will be vital in the implementation of the three fundamental principles of ecological preservation, specialisation, and integrated development. These areas, by going beyond the conventional limits with a three-dimensional breakthrough strategy, eliminating shortcomings by upgrading their infrastructure, intensifying the understanding of the regional brand, and opening up the market through new channels, can turn the ecological resources into economic capital effectively.

Table 5 Table of gradient levels of agricultural production function development

Hierarchy	*C_i value range*	*City*	*Features*
First tier (core zone)	$C_i \geq 0.5$	Hengyang, Yiyang, and Zhuzhou	Possesses an absolute comparative advantage
Second tier (potential zone)	$0.4 \leq C_i \leq 0.5$	Changde, Yongzhou, Changsha, Yueyang, Shaoyang, Loudi, and Chenzhou	Possessing a general comparative advantage
Third tier (nurturing zone)	$C_i \leq 0.4$	Xiangxi Autonomous Prefecture, Huaihua City, Xiangtan City, and Zhangjiajie City	Relatively weaker

3.6 The value function level and distribution characteristics of agricultural production

Table 6 illustrates that the evolution of the agricultural value function in Hunan Province geographically corresponds to the pattern "central prominence with north-south synergy". The three cities with a prefecture-level: Changsha City (0.537), Yongzhou City (0.525), and Chenzhou City (0.508), form the core area, as their agricultural value proximity indices are at the top of the province. The second tier comprises nine prefecture-level cities, including Zhuzhou City and Xiangtan City, which exhibit a 'ring core area' gradient distribution, forming a transitional zone around the first tier. Moderate agricultural development and diverse market rivalry characterise this region. Xiangxi Autonomous Prefecture and Changde City are third-tier with agricultural value function ratings of 0.392 and 0.372. Compared to other prefecture-level cities, Xiangxi Autonomous Prefecture and Changde City need to improve their agricultural value function due to lower growth rates in specialised and supporting activities in agriculture, forestry, animal husbandry, and fishery, and slower primary industry growth.

Table 6 Gradient levels in the development of the agricultural production function

Hierarchy	*C_i value range*	*City*	*Features*
First tier (core zone)	$C_i \geq 0.5$	Changsha, Yongzhou, and Chenzhou	Possesses an absolute comparative advantage
Second tier (potential zone)	$0.4 \leq C_i \leq 0.5$	Zhuzhou, Xiangtan, Hengyang, Shaoyang, Yueyang, Jiading, Yiyang, Huaihua, and Loudi	Possessing a general comparative advantage
Third tier (nurturing zone)	$C_i \leq 0.4$	Xiangxi Autonomous Prefecture, Changde City	relatively weaker

3.7 Discussion

Measurement of agricultural productivity holds value for sustainable development. The productivity of Hunan Province was examined under a set of resources, production capability, structure, and market competitiveness by a recent study. A group of prefecture-level cities, comprising 14, was analysed efficiently by the TOPSIS model, game theory, and weighing methods such as AHP, CRITIC, and Entropy Weighting.

The results indicated large regional differences. Hengyang and Yiyang scored highest for their agro-ecological conditions and basic farmland infrastructures. Xiangtan and Zhangjiajie scored lower for urbanisation, loss of farmland, and poor mechanisation. Value functions of agriculture emphasised all-around development, of which Changsha and Chenzhou ranked highest in performance and competition ability.

Limitations are the reliance on historical data, missing the full impact of climate change and tech advances. Social factors like labour migration were also excluded. Still, the findings provide insights for policymakers, urging leading cities to innovate and lagging ones to enhance infrastructure, mechanisation, and farmland protection. Future research should establish a more comprehensive analytical framework by integrating multi-source data, including satellite remote sensing, climate projections, and socio-demographic statistics. This integration will effectively address current limitations and enhance the rigor of subsequent studies.

4 Conclusions and suggestion

In Hunan Province, agricultural productivity is primarily influenced by production factors and natural resource endowments, with the highest weights assigned to agricultural mechanisation, farmland irrigation, and per capita arable land area – underscoring the critical role of mechanisation and land constraints. Hunan's agricultural development follows three complementary paths: structural optimisation, value enhancement, and competitiveness improvement. Traditional crop farming remains dominant, while per capita disposable income and primary industry growth highlight the dual pursuit of efficiency and equity. Market competitiveness relies heavily on specialty crop cultivation and the share of the primary industry in GDP, reflecting strategies of 'specialisation breakthrough' and 'basic guarantee'.

Spatial analysis reveals substantial disparities in productivity. Hengyang and Yiyang lead due to favourable conditions and advanced mechanisation, while Xiangtan, Zhangjiajie, and Xiangxi lag due to urbanisation pressures and terrain limitations. Core areas such as Hengyang, Yiyang, and Zhuzhou should capitalise on geographic advantages and innovation capacity, whereas potential regions must strengthen industrial chains and value addition. The spatial pattern of agricultural value functions follows a 'central rise, north-south linkage', emphasising differentiated strategies to enhance competitiveness and promote balanced, sustainable agricultural modernisation across Hunan Province. development.

Based on the research findings, we propose the following prioritised policy recommendations: in the short term, the focus should be on advancing agricultural mechanisation in core production areas, strengthening irrigation infrastructure in key agricultural zones, and implementing farmland protection measures in urbanising regions; in the medium term, efforts should shift toward developing specialised crop cultivation systems, enhancing value chain integration for major agricultural products, and promoting agricultural industrialisation in less developed areas; while long-term strategies should centre on establishing an integrated monitoring system for sustainable agricultural development, fostering innovation-driven growth in advanced regions, and strengthening ecological conservation in ecologically vulnerable areas.

Declarations

Author declares that they have no conflicts of interest.

References

Cao, X., Lei, J., Shi, D., Yu, W., Tao, T., Zhang, X. and Wang, A. (2025) 'New quality productivity of agriculture and rural areas at the provincial scale in China: indicator construction and Spatiotemporal evolution', *ISPRS International Journal of Geo-Information*, Vol. 14, No. 3, p.104.

Çelikbilek, Y. and Tüysüz, F. (2020) 'An in-depth review of theory of the TOPSIS method: an experimental analysis', *Journal of Management Analytics*, Vol. 7, No. 2, pp.281–300.

Duan, W. and Pan, Y. (2024) 'Evaluation of the sustainable development level of grain family farms in main grain-producing areas based on agricultural multi-function: a case study of Hunan Province in China', *Frontiers in Sustainable Food Systems*, Vol. 8, p.1459688.

Guo, B., He, D., Zhao, X., Zhang, Z. and Dong, Y. (2020) 'Analysis on the spatiotemporal patterns and driving mechanisms of China's agricultural production efficiency from 2000 to 2015', *Physics and Chemistry of the Earth*, Parts a/b/c, Vol. 120, p.102909.

Kailaku, S.I., Arkeman, Y., Purwanto, Y.A., Udin, F., Amirhusin, B., Wijaya, H., Hidayah, N.J., Hermadi, I. and Hendrawan, V.S. (2025) 'Transforming agroindustry in indonesia: emerging digital technologies for reducing food loss (Chinese and English versions)', *Liang You Shipin Ke-Ji*, Vol. 33, No. 3, pp.47–67.

Krityakierne, T., Sinpayak, P. and Khiripet, N. (2025) 'GIS spatial optimization for agricultural crop allocation using NSGA-II', *Information Processing in Agriculture*, Vol. 12, No. 2, pp.139–150.

Li, J., Zhang, Z., Mao, X. and Zhang, R. (2016) 'Evaluation and suggestions about China agricultural layout based on resources and ecological load', *Issues Agric. Econ.*, Vol. 37, pp.26–33.

Ortiz-Bobea, A., Ault, T.R., Carrillo, C.M., Chambers, R.G. and Lobell, D.B. (2021) 'Anthropogenic climate change has slowed global agricultural productivity growth', *Nature Climate Change*, Vol. 11, No. 4, pp.306–312.

Pan, Y., Lin, Y. and Yang, R. (2022) 'Agricultural production space suitability in China: spatial pattern, influencing factors and optimization strategies', *International Journal of Environmental Research and Public Health*, Vol. 19, No. 21, p.13812.

Pandey, P.C. and Pandey, M. (2023) 'Highlighting the role of agriculture and geospatial technology in food security and sustainable development goals', *Sustainable Development*, Vol. 31, No. 5, pp.3175–3195.

Santos-Martín, F., Zorrilla-Miras, P., García-Llorente, M., Quintas-Soriano, C., Montes, C., Benayas, J., Gómez Sal, A. and Paracchini, M-L. (2019) 'Identifying win-win situations in agricultural landscapes: an integrated ecosystem services assessment for Spain', *Landscape Ecology*, Vol. 34, No. 7, pp.1789–1805.

Sarkar, A. (2013) 'A TOPSIS method to evaluate the technologies', *International Journal of Quality & Reliability Management*, Vol. 31, No. 1, pp.2–13.

Tsai, D-Y., Lee, Y. and Matsuyama, E. (2008) 'Information entropy measure for evaluation of image quality', *Journal of Digital Imaging*, Vol. 21, No. 3, pp.338–347.

Vaidya, O.S. and Kumar, S. (2006) 'Analytic hierarchy process: an overview of applications', *European Journal of Operational Research*, Vol. 169, No. 1, pp.1–29.

Wang, C., Li, Z., Chen, H. and Wang, M. (2023) 'Comprehensive evaluation of agricultural water resources' carrying capacity in Anhui province based on an improved TOPSIS model', *Sustainability*, Vol. 15, No. 18, p.13297.

Xiaobin, J.I.N., Xinyuan, L., Bo, H.A.N., Shilei, W., Buting, H. and Jiapeng, S. (2022) 'Theoretical analysis and geographical support framework of cultivated land protection for Chinese-style modernization', *Economic Geography*, Vol. 42, No. 11, pp.142–150.

Yanbo, Q., Shilei, W., Yaya, T., Guanghui, J., Tao, Z. and Liang, M. (2023) 'Territorial spatial planning for regional high-quality development – an analytical framework for the identification, mediation and transmission of potential land utilization conflicts in the Yellow River Delta', *Land Use Policy*, Vol. 125, p.106462.

Zhang, S. (2022) 'A study on RSR evaluation of health service capacity of county-level administrative areas based on entropy weight TOPSIS method in Fujian Province in China', *MedRxiv*, pp.2010–2022.

Žižović, M., Miljković, B. and Marinković, D. (2020) 'Objective methods for determining criteria weight coefficients: a modification of the CRITIC method', *Decision Making: Applications in Management and Engineering*, Vol. 3, No. 2, pp.149–161.

Zhou, Z., Xiang, C. and Mi, Z. (2019) 'Comprehensive evaluation of sustainable development of urban agriculture in the Changsha-Zhuzhou-Xiangtan urban agglomeration', *Bulletin of Soil and Water Conservation*, Vol. 39, No. 5, pp.278–284.

Yan, L., Sun, Y. and Yang, K. (2025) 'Digital talent empowering new agricultural productivity: logical connections, real-world problems and practical paths', *Journal of Huazhong Agricultural University (Social Sciences Edition)*, Vol. 3, No. 177, pp.87–99.